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Some Comments on the Current State of Econometrics

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Abstract

Regarding the current econometric scene, in this review I argue that (*a*) traditional econometric modeling approaches do not provide a reliable basis for making inferences about the causal effect of a supposed treatment of data in observational and quasi-experimental settings; and (*b*) the focus on conventional reductionist models and information recovery methods has led to irrelevant economic theories and questionable inferences and has failed in terms of prediction and the extraction of information relative to the nature of underlying economic behavior systems. Looking ahead, a nontraditional econometric approach is outlined. This method recognizes that our knowledge regarding the underlying behavioral system and observed data process is complex, partial, and incomplete. It then suggests a self-organized, agent-based, algorithmic-representation system that involves networks, machine learning, and an information theoretic basis for estimation, inference, model evaluation, and prediction.

1. INTRODUCTION

I am indebted to the editors of this volume for giving me, from the vantage point of over seven decades of quantitative economic research, a chance to comment on the current state of econometrics. It is with a great deal of pleasure that I take on this task.

The financial crunch of recent times turned a spotlight on the nature of our inadequate reigning paradigms in macro-, micro-, and econometrics (MME). This recession emphasized the need to rethink each area with a multifaceted critical discussion, investigate what failed, and consider how to implement a repair. Certainly, reforming the standard form in each area would be a welcome event, because in my opinion all of the important players in terms of information recovery and prediction have failed. Over time, the MME knowledge slices have become so thin that the sum of the parts does not serve as a basis for understanding and making predictions concerning the parts of the whole.

The academic pursuit of economic self-interests does not lead, as if by an invisible hand, to an understanding of the hidden, complicated dynamics underlying economic processes and systems. In many cases, analytical reductionist economic and econometric models, whether relevant or not, are an end result, and in the classroom and in print, they take on a life of their own. Although many of societies' economic ills are not well served by the unhappy state of micro- and macroeconomics, my focus is on the current state of affairs and what this may mean in terms of rethinking econometrics.

2. THE INFORMATION RECOVERY PROBLEM

Faced with the challenges of understanding complexity, uncertainty, volatility, and ambiguity, current conventional econometric models and methods have told us more about the unpredictability of economic–behavioral processes than about how to understand and predict them. The econometric–statistical complexity of information recovery emerges, because economic systems are dynamic and seldom in equilibrium. No unique time-invariant econometric model is capable of capturing these aspects. Given an uncontrolled sample of effects data that is indirect, noisy, and observational in nature, it remains unclear how to use this information to choose a member from the family of economic and econometric models that reflects the unknown initial condition and the hidden dynamics of the economic process. In fact, it is not clear that choosing a member from the collection of incorrect models is even the right question.

In attempts to learn from a sample of indirect noisy data, the traditional approach in econometrics usually has a "what is" focus. What is the model? What is the set of parameters? What is the sampling distribution underlying the sample of data? There is something troubling about this approach as an econometric basis for learning from an observed uncontrolled data sample. To ask what the parameter or underlying likelihood–density function is, rather than what it could be, would seem to ask an incorrect and unnecessarily difficult question. The underlying econometric framework is conceptual in nature and seldom, if ever, correctly specified. The parameters, structural or otherwise, are unobserved and indeed are unobservable.

Sample information based on indirect noisy sample observations comes from economic systems or processes that are, in general, not in equilibrium. Although only one sampling distribution is consistent with an economic system in equilibrium, there are many possible ways an economic process system may be out of equilibrium. For many econometric problems and data sets, the natural solution may not be a fixed distribution, but rather a set of distributions, each with its own probability. In this situation, the value of an econometric prediction, similar to that of a gambler facing a loaded die, is related to how far the system is out of equilibrium.

The resulting uncertainty about existing conditions and the dynamics of the process create problems for econometric model specification. This hinders traditional direct econometric methods from capturing the underlying hidden structure or key dynamic functions of the economic system. Although economic processes are, in general, simple in nature, the underlying dynamics are complicated and not well understood. The result is a family of economic models, each incorrectly specified and containing inadequacies that provide an imperfect link to the indirect noisy observational data.

Because the data associated with information recovery in a dynamic economic system generally consist of a sample of observations of indirect noisy effects, distinguishing between mutual influence and causal influence to uncover dynamic or directional information is impossible. Even introducing a lag in the mutual observations fails to distinguish information that is actually exchanged from shared information and does not support time causality. It is important to acknowledge that lags are simply functions of the known past that are artificially reversed and added to the present value of the function. Furthermore, in quasi-economic experiments that are currently popular, the underlying noisy data variability usually dominates the causal effects one hopes to measure.

With indirect noisy observations, any attempt to identify the underlying dynamic system and to measure causal influence requires the solution of a stochastic inverse problem. This is the inverse of the conventional forward problem that relates the model parameters to the observed data. Thus, the data are in the effects domain while our interest lies in the causal domain. If the number of data points is smaller than the number of unknown parameters to be estimated, the stochastic inverse problem is ill posed. Without a large number of assumptions, the resulting stochastic ill-posed, underdetermined inverse problem cannot be solved, using the rules of logic, by traditional estimation and inference methods. As a result, conventional semi- and parametric estimation and inference methods are fragile under this type of model and data uncertainty. In general, they are not applicable for answering causal influence questions about dynamic economic systems. The application of traditional econometric models and methods that are not suited to the ill-posed inverse information recovery task have led to what Caballero (2010) calls a pretense of knowledge syndrome.

3. COPING WITH THE UNCERTAINTY OF UNCERTAINTY

One way to handle the stochastic inverse information recovery problems is to use estimation and inference methods designed for that purpose. In this context, an information theoretic entropy–based multiparametric family of likelihood functions provides a basis for linking the data and the macro- and micromodel parameters. This entropic family of power divergence measures encompasses a family of test statistics that leads to a broad family of likelihood functions within a moments–based estimation and inference context. This class of information theoretic estimation and inference procedures (Judge & Mittelhammer 2011, 2012; Mittelhammer & Judge 2011) permits one to gain insight on the probability-density-function (PDF) behavior of dynamic economic systems and processes. Likelihood functional-PDF divergences have an intuitive interpretation in terms of uncertainty and measures of distance. Information theoretic dynamic economic models appear naturally and can be given a directional meaning in a conditional Markov framework when state spaces and transition probabilities are introduced in the information theoretic framework (Miller & Judge 2015). This type of traditional information theoretic formulation lets us get a peek at the dynamics of the system and introduces the role of time in causality. If one chooses to remain in the traditional econometric model framework, the information theoretic recovery methods offer an improved basis for handling some of the many problems noted above.

Unfortunately, few econometricians are aware of and make use of this information theoretic basis of estimation and inference.

Finally, let us consider the current situation. Using traditional econometric methods since the 1940s, we have survived approaches, such as the MIT-Federal Reserve type large-scale econometric models; vector auto regressions; rational expectations; the arbitrariness of calibration that essentially picks a few parameters that may match a few arbitrarily chosen moments or empirical regularities; and the current dynamic stochastic general equilibrium macromodel. In views of the economic world, we have been treated to general equilibrium, partial equilibrium, the optimum guiding hand equilibrium of Adam Smith, game theoretic solutions, and many other possible convex combinations. The agonizingly slow process of economic–econometric knowledge and information recovery has resulted in many models being spawned, and often the models actually become the end result because the truth or falsity of the models can never be checked. The surviving theoretical models take on a life of their own, and graduate students receive the same old tired economic and econometric models and solutions decade after decade. Although a major desired component of economic information is on causal influence recovery, the intersection of this objective with indirect noisy effects data and traditional direct econometric methods leads in many cases to an empty set. The task of moving economics–econometrics in the direction of a probabilistic and predictive science is a goal yet to be achieved.

4. SPECULATIONS ON THE ECONOMETRIC ROAD AHEAD

In the previous section, I argued that (*a*) traditional econometric modeling approaches do not provide a reliable basis for making inferences about the causal effect of a supposed treatment of data in observational and quasi-experimental settings, and (*b*) the focus on conventional reductionist models and information recovery methods has led to irrelevant economic theories and questionable inferences. We have failed in terms of the prediction and extraction of information relative to the nature of underlying economic behavior systems.

As we look to the future, I recognize a second path to econometric information recovery that is outlined in this section. The traditional path, which I discussed in Sections 2 and 3, starts by assuming a stochastic model based on economic, econometric, and inferential statistics foundations. The unknown and unobservable parameters of the assumed structured-stochastic model are estimated from a relevant sample of observed data and used for inference and prediction. The other approach, which is emphasized in this section, recognizes our knowledge regarding the underlying behavioral system. The observed data process is complex, partial, and incomplete and uses a self-organized, agent-based representation system involving networks and an information theoretic basis for estimation, inference, model evaluation, and prediction. In the following paragraphs, I discuss ways in which combining information theoretic methods in a self-organized, systems-problem framework may contribute to the accumulation of economic–econometric knowledge.

As we seek new nontraditional ways to think about the causal adaptive behavior of complex and dynamic microsystems, we may use causal entropy maximization as the systems status-criterion measure. This follows Wissner-Gross & Freer (2013) in how to make a connection between adaptive intelligent behavior and causal entropy maximization (AIB-CEM). In this context, each microstate appears as a causal consequence of the macrostate, to which it belongs. This permits us to recast a behavioral system in terms of path microstates, where entropy reflects the number of ways a macrostate can evolve along a path of possible microstates. The more diverse the number of path microstates is, the larger the causal path entropy can be. A uniform-unstructured distribution of the microstates corresponds to a macrostate with maximum entropy and minimum information. The result is a causal entropic approach that captures self-organized, equilibrium-seeking behavior.

In this setting, the unknown choices are behavior-related in the same sense that data do not behave, but people do. (I learned this basic bit of economic knowledge from Kenneth Boulding in 1948 when he chastised me for saying that prices did such and such and said, “Son, prices do not behave, people behave.”) As a framework for predicting nontraditional agents’ choices, this permits us to consider self-organized, equilibrium-seeking AIB-CEM behavioral systems and to use information theoretic-based methods to solve the resulting ill-posed stochastic inverse problem and to recover estimates of the unknown behavioral parameters.

In coping with the associate recovery problems, a natural solution is to use information theoretic estimation and inference methods that are designed to deal with the nature of economic–econometric models and data, as well as the resulting behavioral stochastic inverse problem. In this context, the family of distribution-entropic functions described by Cressie and Read (Cressie & Read 1984, Read & Cressie 1988) provides a basis for linking the data and the unobserved and unobservable behavioral model parameters. This permits the researcher to exploit the statistical machinery of information theory to gain insights relative to the underlying adaptive-causal behavior of a dynamic system that may not be in equilibrium. Thus, in developing an information theoretic econometric approach to estimation and inference, the single parameter family of entropic functions represents a way to link the likelihood-entropic behavior informational functions with the underlying sample of data to recover estimates of the unknown parameters. Information entropic functions of this type have an intuitive interpretation that reflects uncertainty as it relates to a model of the adaptive behavior for economic–econometric processes.

In identifying estimation and inference measures that may be used as a basis for characterizing the data sampling process for indirect, noisy observed data outcomes, we use the multiparametric, convex family of entropic functional power divergence measures:

$$I(\mathbf{p},\mathbf{q},\gamma) = \frac{1}{\gamma(\gamma+1)} \sum_{i=1}^{n} p_i \left[\left(\frac{p_i}{q_i} \right)^{\gamma} - 1 \right]. \tag{1}$$

In Equation 1, the parameter γ indexes members of the Cressie-Read (CR) family, p_i represents the subject probabilities, and q_i is interpreted as a reference probability. Being probabilities, the usual probability distribution characteristics of $p_i, q_i \in [0, 1] \forall i$, $\sum_{i=1}^{n} p_i = 1$, and $\sum_{i=1}^{n} q_i = 1$ are assumed to hold. In Equation 1, as γ varies, the family of estimators that minimize power divergence exhibits qualitatively different sampling behavior that includes Shannon’s entropy, the Kullback-Leibler measure, and in a binary context, the logistic distribution divergence (see Gorban et al. 2010; Judge & Mittelhammer 2011, 2012). In identifying the probability space, the family of power divergences is defined through a class of additive convex functions and leads to a broad family of likelihood functions and test statistics. The CR measure exhibits proper convexity in $\mathbf{p}$ for all values of γ and $\mathbf{q}$ and embodies the required probability system characteristics. In the context of extremum metrics, the general entropic family of power divergence statistics represents a flexible family of pseudo-distance measures from which to derive the unknown system empirical probabilities. To demonstrate the applicability of this type of nontraditional approach, we may for example use an information theoretic estimation and inference framework as a basis for (*a*) recovering the optimum solution for the unknown pathway probabilities of a general binary behavioral network (Cho & Judge 2014, Judge 2015), (*b*) a nonlinear ordinal basis for recovering patterns in times series data (Judge 2013, 2015; Zanin et al. 2012), and (*c*) hidden Markov processes (Miller & Judge 2015).

5. A FINAL REMARK

Looking back, I am gratified by how far we have come, but I am also disappointed that a more useful framework for information recovery continues to elude us. The resulting implication is that unless we develop and apply nontraditional econometric methods of information recovery that are appropriate to the data and economic problems and questions at hand, our ability to understand and recover empirical system probabilities and to provide accurate predictions about dynamic economic processes will continue to be uninformed and limited. Furthermore, our brightest and best graduate students will continue to be taught econometric history instead of considering new ways of quantitative information recovery.

Perhaps it is important to underscore again the partial, incomplete, and incorrect nature of traditional economic–econometric models. This raises a question of whether measurement with theory can consistently explain our hidden dynamic world of interest. Economic information recovery requires new modeling and econometric methods of the type discussed in Section 4 if we are to understand the underlying dynamic economic systems that generate the indirect noisy data that we observe. Although it is too early and too simplistic to declare an end to theory, we should remind ourselves that our diligent pursuit of measurement with traditional information recovery methods has in many cases reduced econometrics to data fitting and does not represent a very useful version of the economic world we seek to understand. Perhaps the questionable compatibility of traditional econometric methods and the nature of new forms of observable data will be instrumental in instigating change.

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